Exploratory Data Analysis Reveals Spatio-temporal Structure of Null fMRI Data

R. Baumgartner, L. Ryner, R. Somorjai, R. Summers
Institute for Biodiagnostics, National Research Council Canada, Winnipeg, Manitoba, Canada

Introduction: Exploratory data analysis (EDA) as developed in computational statistics (2) provides methods for exploration of multidimensional data structures. It is conceptually different from the classical statistical confirmatory methods as it aims to let the data speak for itself. However, once the structure of the data is revealed, the question must be asked: do the structures arise only by chance, or do they actually reflect some real effect? Here we investigated the application of EDA tools to in vivo fMRI data analysis in a systematic study with varying sampling rate. fMRI data were acquired under the null hypothesis, i.e. no activation.

Materials and Methods Water phantom: Five (2D) data sets were acquired with the following parameters: FA/TE/MA = 60/50/128x128, and with TR variation TR = 334/625/1250/2500 ms (note that TR may be considered as the sampling frequency of the physiological effects).

In vivo fMRI data acquired under null condition: Three healthy subjects were investigated. For each subject, five in vivo data sets were acquired with the same parameters as for the water phantom. EDA (Preprocessing): Our aim was to divide the fMRI time-courses (TCs) into two groups. The first group consisted of those TCs that are contaminated by white noise and the second comprised TCs that were either contaminated by colored (physiological) noise or contain the signal of interest. To separate the two types of TCs the 1-lag (r1) and 2-lag (r2) Pearson autocorrelation coefficient was calculated for each TC. Then a r1-r2 plot was created (the horizontal and vertical axes correspond to r1 and r2, respectively). For white data this plot is symmetrically distributed in a disk around the origin of the coordinate system. Spatial distribution of the non-white TCs was also displayed.

Fuzzy Clustering EDA (4,5) was applied in the time domain only to those TCs that survived the preprocessing step, in order to investigate their temporal behaviour across the TR range.

Results and Conclusion: In Fig. 1 the r1 maps obtained from the in vivo data for the TRs: (a) 3500, (b) 2500, (c) 1250, (d) 625, (e) 335 ms. The water phantom r1-map (f) is also displayed.

Fig. 2 The r1-r2 plots for the in vivo data (a, b, c, d, e) as in Fig. 1 and the water phantom (f). Arrows point to the regions where the r1-r2 plots are deformed due to colored noise.

In Fig. 2 the r1-r2 plots for in vivo data (a, b, c, d, e) as in Fig. 1 and the water phantom (f) are shown. The r1-r2 plot for the water phantom is symmetrically distributed around the origin of the coordinates (OC). For in vivo data the r1-r2 plots are deformed and contain of two parts. One which is symmetrically distributed around the OC as in the case of water phantom and another one which appears as a tail in the upper right corner of this plot. These points correspond to the pixels highly contaminated by autocorrelated physiological noise. To identify them a threshold based on statistical significance of the r1 was used (p-value=0.05). The TCs of the survivors were used as an input to FCA. For all subjects investigated FCA was able to detect various kinds of physiological noise artifacts for each TR and consistent tendencies could be identified. For low TR (high sampling frequency), breathing and heart beat artifacts were identified. The higher the TR, the more the TCs were contaminated by trends. As the regions contaminated across the TR range overlap, this suggests aliasing from higher frequencies as the sampling rate (TR) approaches the Nyquist barrier. Systematic investigation of the aliasing patterns in fMRI time-series is an important challenge for better identification of "true activations" in fMRI (6). We showed that EDA-based methods that do not require prior knowledge about the spatio-temporal shapes of the TCs offer valuable tools for MR time-series (spatio-temporal) artifact detection.

References